Journal Evaluation in Education (JEE)
Vol. 5, No. 4, October 2024, pp. 144~154
ISSN: 2716-4160, DOI: 10.37251/jee.v5i4.1151

Education in the ChatGPT Era: A Sentiment Analysis of Public Discourse on the Role of Language Models in Education

Niel Francis B. Casillano[1]
[1]Department of Information Technology, College of Computer Studies, Eastern Samar State University, Philippines

Article Info

Article history:

Received Sep 09, 2024
Revised Sep 29, 2024
Accepted Oct 20, 2024
OnlineFirst Oct 29, 2024

Keywords:

Chatgpt
Language Model
Sentiment Analysis
Topic Modelling
Vader

ABSTRACT

Purpose of the study: This research explored the public discourse on the role of language models in education, particularly ChatGPT.

Methodology: The study employed sentiment analysis, word cloud analysis, and thematic analysis of YouTube video news transcripts.

Main Findings: The study identified key themes and public perceptions surrounding AI's role in education. The analysis revealed frequent mentions of AI, education, and learning, highlighting AI's transformative potential in personalizing education and improving administrative efficiency. The study also emphasizes significant concerns about academic integrity, with terms like cheating and plagiarism reflecting ethical apprehensions. The sentiment analysis revealed a compound sentiment of 0.866, a generally positive perception of AI's impact on education. However, some negative sentiments were recorded, particularly around data privacy and potential biases. The thematic analysis identified five key topics: the future of AI and human intelligence, AI in education and learning enhancement, innovative teaching tools and technologies, AI-assisted writing and learning tools, and ethics and academic integrity in AI usage. The findings revealed the importance of developing robust ethical guidelines and policies for integrating AI into educational settings and the need for further research into the long-term impacts of AI on teaching methodologies.

Novelty/Originality of this study: The research used YouTube news transcripts to explore public discourse on ChatGPT's role in education, providing real-time insights into societal perceptions. Combining sentiment, word cloud, and thematic analyses offers a balanced examination of the transformative potential and ethical concerns surrounding AI in education.

Corresponding Author:
Niel Francis B. Casillano,
Department of Information Technology, College of Computer Studies, Eastern Samar State University,
National Hwy, Borongan City, 6800 Eastern Samar, Philippines
Email: nfcasillano@gmail.com

1. INTRODUCTION

The educational landscape in the 21st century has undergone rapid transformations, primarily driven by technological advancements, including artificial intelligence (AI) [1], [2]. The recent advancements and growth in machine learning have paved the way for more sophisticated innovations in technology, particularly in the realm of generative artificial intelligence (GAI) for digital content generation [3]. Generative modeling artificial intelligence (GAI) operates within an unsupervised or partially supervised machine learning framework, utilizing statistical and probabilistic approaches to generate artificial artifacts [4]. Through the evolution of deep learning (DL), generative AI has the ability to produce artificial contents by analyzing and learning patterns and distributions from existing digital content, such as video, images/graphics, text, and audio [5]. The dynamic nature of these advancements highlights the transformative impact of technology on educational practices in the contemporary era.

ChatGPT, a recently developed conversational chatbot engineered by OpenAI [6], has the potential to simplify the integration of AI into teaching and learning for instructors. Utilizing natural language processing, ChatGPT generates responses that closely resemble human language in response to user input. Its global recognition stems from its remarkable ability to produce coherent, systematic, and informative responses, capturing attention for its outstanding performance [7]. The advent of language models like ChatGPT has brought about unprecedented opportunities and challenges within the realm of education. As educational institutions, professionals, and enthusiasts explore the potential applications of these language models, it becomes crucial to understand the sentiments expressed in public discussions. While public opinion including that of experts perceive ChatGPT and other extensive language models as valuable tools for enhancing efficiency and precision in writing and conversational tasks, there are concerns raised about potential bias stemming from the training datasets. This bias could constrain ChatGPT's capabilities and lead to factual inaccuracies. Additionally, the scientific and academic communities need to carefully address security concerns related to cyber-attacks and the dissemination of misinformation through large language models like ChatGPT [8].

The intersection of technological disruption and educational practices is not new, with past examples like Google and Massive Open Online Courses facing scrutiny for their impact on cognitive processes and business model issues. These concerns are applicable to ChatGPT, a technology with both considerable potential and significant risks [9], [10]. The application of ChatGPT in education during the digital era has garnered significant attention recently [11]. As an AI-powered chatbot, ChatGPT holds the potential to transform the dynamics of interactions and learning between students and educators. However, a comprehensive understanding of its impact requires a thorough examination of the perspectives of the public regarding the integration of ChatGPT into educational settings [12].

Despite the growing discourse surrounding ChatGPT's potential in education, there exists a research gap in understanding public sentiments, biases, and concerns. This study aims to address this gap by conducting a sentiment analysis on publicly available transcripts of news discussions regarding ChatGPT's impact on education. Specifically, the study aims to: (1) extract transcripts of news videos on ChatGPT and education using an automated transcript extractor; (2) preprocess the collated news transcripts; (3) determine the most frequently used words in the collection of transcripts; (4) determine the overall sentiment of the transcripts using VADER, a sentiment analysis tool; and (5) unveil prevailing and emerging themes within the collection of transcripts. Sentiment analysis, a subset of natural language processing (NLP), seeks to understand sentiments and opinions expressed in text concerning particular entities and topics, such as individuals, organizations, or events. It focuses on classifying texts into positive, neutral, or negative categories [13]. By analyzing these sentiments, researchers can gain insights into how various stakeholders perceive the role of language models in education, whether with optimism, skepticism, or a combination of both. Understanding public discourse is pivotal for policymakers, educators, and technology developers to make informed decisions regarding the integration of language models like ChatGPT into educational settings.

2. RESEARCH METHOD

This study employed a sequential exploratory design incorporating content analysis of online documents. This design, featuring qualitative and quantitative phases, offers flexibility by allowing the researcher's theoretical perspective to shape and guide the study, controlling the sequence of data collection. The integration of results from both methods occurred during the interpretation phase at the study's conclusion [14]. To execute this design, unsupervised machine learning was utilized. Unsupervised learning, a machine learning algorithm, draws inferences from datasets lacking labeled responses. Cluster analysis, a prevalent unsupervised learning method, was specifically employed for exploratory data analysis, revealing concealed patterns or groupings within the data. These groups are modeled using a measure of similarity, defined by metrics such as Euclidean or probabilistic distance [15].

This As can be gleaned in figure 1, the research will commence by extracting transcripts from YouTube news videos discussing the influence of ChatGPT on education, utilizing an online automated transcript extractor. Following extraction, the transcripts will undergo the preprocessing phase, involving the removal of timestamps, non-textual elements, stemming, stop words removal and redundancy to ensure clarity and relevance. Subsequently, sentiment analysis was conducted using the Valence Aware Dictionary and Sentiment Reasoner (VADER) to gauge public sentiments expressed in the transcripts. The data then underwent topic modeling using Latent Dirichlet Allocation (LDA) to identify key themes and topics within the discussions. The generated themes were further subjected to thematic analysis, allowing for a comprehensive understanding of the prevalent sentiments and recurrent topics in the public discourse surrounding ChatGPT's impact on education. This integrated process aimed to unveil insights into the diverse perspectives and prevalent themes expressed in the YouTube discussions on the intersection of ChatGPT and education.

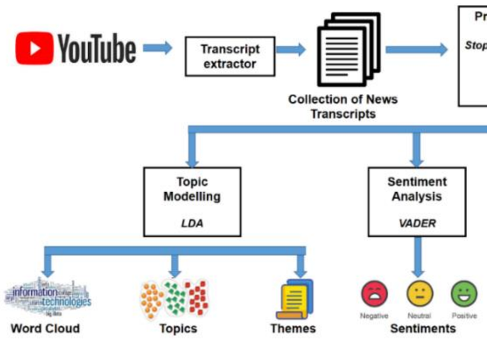

Figure 1. Research Paradigm

Data collection entails the utilization of an online automated transcript extractor to extract text from YouTube news video transcripts that discuss the influence of ChatGPT on education. The process involves deploying the automated tool to systematically extract relevant textual content from the videos. Subsequently, the extracted data undergoes cleaning and preprocessing, addressing any format inconsistencies introduced during the extraction. Each transcript will be named as tr1, tr2, tr3 and so on. The transcripts will be saved as a text (.txt) file and will be loaded into Orange Data Mining Software. All transcripts will undergo text preprocessing and cleaning. In the preprocessing stage, information extraction from the documents is performed to identify keywords and relationships within the text this is also known as pattern matching. This technology is very advantageous when dealing with large volumes of text. The preprocessing and cleaning methods that will be performed in this research are: **Stopwords Removal:** In natural language processing, stopwords are common words that do not contribute significantly to the meaning of a text. These words, such as articles, prepositions, and pronouns, are often removed from a text to reduce its dimensionality and make it easier for analysts to process. Removing stopwords helps to simplify the text and make it more focused on the essential information [16]. **Stemming:** Stemming is a method used to identify the root or stem of a word. For example, words such as "connect," "connected," "connecting," and "connections" can all be traced back to the root word "connect" [17]. The goal of stemming is to reduce the number of words in a text, improve the precision of matching stems, and conserve time and memory resources. **Term Frequency-Inverse Document Frequency (TF-IDF):** TF-IDF is a numerical statistic used to assess the importance of a word in a collection of documents. It is widely used in information retrieval and text mining and is calculated by taking into account the frequency of a word in a document and balancing it with its frequency in the entire corpus. A word with a high TF-IDF score is considered to be important and relevant to the collection of documents [16]. In the calculation of TF-IDF using the formula contained in the following equation [18].

a. Calculate the value of TF by using equation (1) as follows:

$$TF(i,j) = \frac{freq(i,j)}{max_{ki,kj}} \quad \ldots (1)$$

b. Calculate the IDF value using equation (2) as follows:

$$IDF(i) = log_2\left(\frac{N+1}{n_1+1}\right) + 1 \quad \ldots(2)$$

c. Calculate the value of TF-IDF by using equation (3) as follows:

$$TF - IDF(i,j) = TF_{(i,j)} * IDF_{(i,j)} \quad \ldots(3)$$

Sentiment analysis, an NLP technique, involves assessing the sentiment of a text, determining whether it is positive, negative, or neutral; and tools like Vader, a rule-based sentiment analysis tool specifically crafted for social media texts, utilize pre-trained models, employing a dictionary of words and rules to assign valence scores, ranging from -4 to +4, indicating positivity or negativity. In this study, sentiment analysis was conducted using the Valence Aware Dictionary and Sentiment Reasoner (VADER), a rule-based tool finely tuned for social media and text sentiments. This open-source utility, is integrated into the NLTK package, allowing for immediate application to unlabeled text data. VADER considers word order and degree modifiers, exhibiting sensitivity to both emotion polarity (positive/negative) and intensity. The model provides sentiment scores for each category (negative, neutral, and positive) based on the polarity metric, ranging from -1 (indicating negativity) to +1 (indicating positivity). Adverbs, serving as modifiers, influence the intensity of words. The compound score, summing up all sentiment scores and ranging from -1 to +1, serves as an aggregate measure, aiding in the comprehension of user sentiments. This approach is valuable for understanding nuanced sentiments in various contexts [19], [20]. As explained by [21], VADER employs specific rules, known as heuristics, to account for the influence of each sub-text on the perceived intensity of sentiment in sentence-level text. These heuristics, surpassing the typical scope of a bag-of-words model, incorporate word-order sensitive relationships between terms. The compound VADER scores offer a comprehensive metric for sentiment analysis, computed by summing valence scores adjusted by the heuristics. The resulting compound score is normalized between -1 (most extreme negative) and +1 (most extreme positive), providing a valuable unidimensional measure of sentiment for a given sentence.

LDA, a widely recognized method for topic modeling, was initially introduced in 2003. This unsupervised generative probabilistic model portrays topics through word probabilities. The fundamental function of LDA involves representing documents as random mixtures over latent topics, each characterized by a distribution over words. LDA posits that every document can be depicted as a probabilistic distribution over latent topics, as illustrated in Figure 2. Throughout this process, the topic distribution in all documents shares a common Dirichlet prior. Each latent topic in the LDA model is also portrayed as a probabilistic distribution over words, with word distributions of topics sharing a common Dirichlet prior. In the context of a corpus *D* comprising *M* documents, where document d has N_d words (d ∈ 1, . . . ,M), LDA models *D* according to the subsequent generative process [22], [23]: (a) Choose a multinomial distribution ϕt for topic t (t ∈ {1, . . . , T}) from a Dirichlet distribution with parameter β; (b) Choose a multinomial distribution θd for document d (d ∈ {1, . . . ,M}) from a Dirichlet distribution with parameter α; (c) For a word wn (n ∈ {1, . . . , N_d}) in document d, i) selection of a topic zn from θd, ii) selection of a word wn from ϕzn.

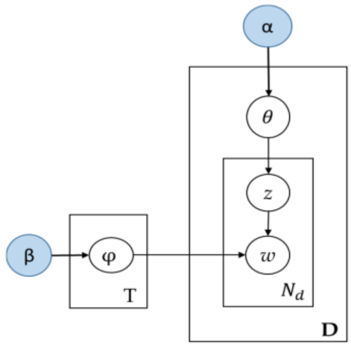

Figure 2. LDA Model

Concerning the generative process outlined earlier, words within documents are considered observed variables, while latent variables (ϕ and θ) and hyperparameters (α and β) remain unobservable. To derive the latent variables and hyperparameters, the probability of the observed data D is calculated and maximized through the following procedure.

$$p(D|\alpha,\beta) = \prod_{d=1}^{M} \int p(\theta_d|\alpha)\left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn}|\theta_d)p(w_{dn}|z_{dn},\beta)\right)d\theta_d \quad \text{…(4)}$$

The α parameters, determining the topic Dirichlet prior and the distribution of words among topics drawn from the Dirichlet distribution, are denoted by β. Here, T represents the number of topics, M denotes the quantity of documents, and N signifies the size of the vocabulary. The consideration lies in the Dirichlet multinomial pair for corpus-level topic distributions (α, β). Additionally, the Dirichlet multinomial pair for topic-word distributions is characterized by β and ϕ. The variables θd pertain to document-level variables, while zdn and wdn represent word-level variables sampled for each word in every text document. Numerous studies across various fields, including linguistic science, political science, medical and biomedical research, and other domains, have explored topic models utilizing LDA [24].

Purposive sampling was employed to ensure the selection of relevant and credible YouTube videos for analysis. The videos were chosen based on the following criteria: they must have been uploaded recently to reflect current discussions, contain both "ChatGPT" and "Education" in their title to focus on the intersection of these topics, and be published by verified news agencies to ensure the reliability and authority of the source. This approach was used to capture accurate and up-to-date perspectives on the role of ChatGPT in education.

The data for this research is derived from transcripts obtained from YouTube news videos, specifically focusing on discussions pertaining to the transformative impact of ChatGPT on education. The selection of YouTube as the primary source is motivated by its widespread use as a platform for news dissemination and public discourse. To compile the dataset, we utilized an online automated transcript extractor, ensuring efficiency and accuracy in the extraction process. The inclusion criteria for videos were defined based on relevance to the research topic, encompassing discussions, analyses, and expert opinions on the integration of ChatGPT in educational settings.

Deciphering topics derived from a topic model poses a more complex challenge than initially perceived. Understanding the precise connotation of a set of words necessitates a profound understanding of their usage within the dataset and the intended contextual meaning. Clearly, the context holds substantial significance when employing unsupervised or semi-supervised methods. Words that appear in one set of survey responses might carry a distinct meaning in another set, and the interpretations ascribed to topics generated by a model trained on one dataset may not seamlessly apply to another. Given that algorithms, such as topic models, lack an inherent understanding of document context, including collection methods and semantics, researchers must adeptly adjust their interpretation based on their understanding of the language utilized in the dataset [25]. The researcher will aim to provide a comprehensive description of the findings and engage in a thorough discussion about the phenomena revealed and supported by the literature. The discussion will strive to address the gaps identified in the introduction, delving into the underlying reasons behind the observed results, and suggesting potential solutions. This will be achieved by answering questions such as how the findings came about, why they happened, and what can be done to address them.

In this research, the text processing, topic modeling, sentiment analysis, and word cloud generation will be conducted using the Orange Data Mining Software. Orange stands out as an open-source platform for machine learning and data visualization, offering an intuitive and visually appealing interface. Recognized for its extensive array of tools and features, Orange facilitates the creation of data analysis workflows [26].

In conducting this research, ethical principles will be central to every stage of the study. While the data that will be used will be derived from publicly available YouTube transcripts, respecting user privacy is paramount. No explicit consent will be obtained, given the nature of online content, but measures will be taken to anonymize information and uphold ethical standards. The study will acknowledge potential biases associated with the YouTube platform's user demographics, committing to addressing these biases transparently in the analysis to ensure a fair representation of perspectives on ChatGPT in education. Additionally, the research embraces open science by providing clear documentation of methodologies, tools, and data sources, fostering transparency and reproducibility. Responsible use of technology, particularly in the context of AI models like ChatGPT, is a core commitment, aiming to contribute to a nuanced understanding of public sentiment while encouraging ethical considerations in the deployment of such technologies in educational settings.

3. RESULTS AND DICUSSION

3.1 Word Cloud Results

The word cloud analysis, as seen in figure 3, revealed that the most frequently occurring words were: AI, education, learning, think, writing, cheating, future, improve, plagiarism, tool, access. AI's prominence highlights its transformative potential, with discussions on the transcripts centering on enhancing learning experiences, personalizing education, and improving administrative efficiency [27]. The frequent mention of "education" and "learning" underscores the sector's evolving landscape due to AI integration, emphasizing the core objective of facilitating adaptive learning experiences this consistent with the research of [28] mentioning that AI's potential impact on education is multifaceted. However, significant concerns arise around academic integrity, with "cheating" and "plagiarism" reflecting apprehensions about the misuse of AI, raising ethical issues in academic assessments. Cotton et al. [29] said that AI in higher education presents both opportunities and challenges. Furthermore, Miao et al. [30] said that AI-generated text in academic manuscripts can undermine academic integrity. The future-oriented discussions, marked by "future" and "improve," indicate optimism about AI's long-term impacts and potential enhancements in teaching methodologies and learning outcomes. The terms "tool" and "access" highlight the practical applications of AI in supporting educators and ensuring equitable access to educational resources, addressing the digital divide. These insights imply a need for robust policies to maintain academic integrity, ongoing research and investment in AI technologies, and professional development programs to train educators in AI tool usage. Moreover, ethical considerations, particularly regarding data privacy and bias, must be addressed through comprehensive policies and frameworks to ensure responsible AI use.

Figure 3. Word Cloud

3.2 Sentiment Analysis Results

The sentiment analysis heat map shown in figure 4, with blue indicating negative sentiment and yellow indicating positive sentiment, reveals that the majority of articles were rated as positive. This is evident from the compound sentiment score of 0.866 (shown in table 1), which falls within the positive range. This result suggests a generally favorable public perception of ChatGPT's impact on education, with many stakeholders viewing its potential to enhance learning experiences, improve educational outcomes, and facilitate administrative tasks positively. This findings is consistent with [31] stating that Implementing ChatGPT in the educational environment has a positive impact on the teaching-learning process. However, the presence of some negative sentiments indicates concerns about issues such as academic integrity, data privacy, and potential biases in AI applications. The positive sentiment overall implies that educators, policymakers, and technology developers might feel encouraged to further explore and integrate AI technologies in educational settings, but they must also address the highlighted concerns to ensure ethical and effective implementation. Balancing innovation with ethical considerations will be crucial for maximizing the benefits of AI while mitigating its potential drawbacks.

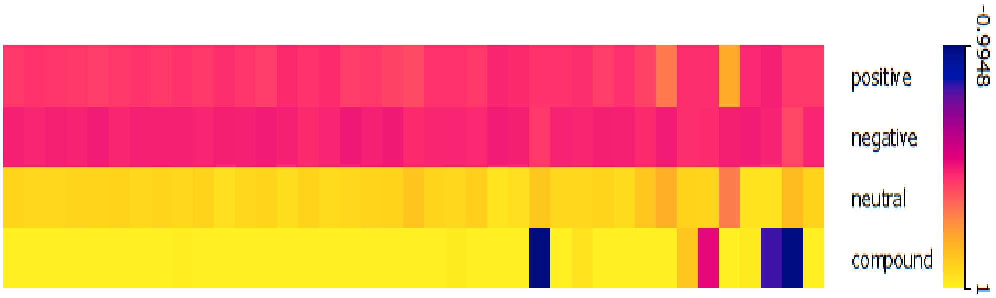

Figure 4. Heat Map

Table 1. Average Sentiment Scores of the Extracted Scripts

Positive	Negative	Neutral	Compound
0.120	0.046	0.835	0.866

3.3. Topic Modelling Results

The thematic analysis of the YouTube video transcripts discussing ChatGPT's impact on education revealed five key topics, each characterized by a set of prominent keywords. These topics not only reflect the diverse perspectives within the public discourse but also highlight the prevailing sentiments and concerns associated with the integration of AI in educational settings.

As can be gleaned in table 2, topic 1, "Future of AI and Human Intelligence," explores the broader implications of AI on human intelligence and its anticipated long-term impacts on various aspects of life and work. Topic 2, "AI in Education and Learning Enhancement," focuses on the potential benefits of AI in improving educational experiences and learning outcomes, highlighting how AI can transform traditional methodologies. Topic 3, "Innovative Teaching Tools and Technologies," emphasizes the integration of AI tools like ChatGPT into classrooms, showcasing their role in revolutionizing teaching practices and enhancing educational delivery. Topic 4, "AI-assisted Writing and Learning Tools," delves into AI's role in assisting with writing and other learning tasks, discussing its capability to generate written content and improve language skills. Topic 5, "Ethics and Academic Integrity in AI Usage," addresses the ethical considerations and challenges associated with AI in academic settings, expressing concerns over academic integrity and the potential misuse of AI tools in ways that could compromise educational values and ethics.

Table 2. List of Generated Topics

Topic	Keywords	Topic Label/Theme
Topic 1	*years, actually, people, ai, would, intelligence, work, chatgpt, right, happen*	Future of AI and Human Intelligence
Topic 2	*ai, students, chatgpt, education, learning, future, improve, think, study, better*	AI in Education and Learning Enhancement
Topic 3	*chatgpt, school, teacher, new, tool, technology, teach, ai, students, innovation*	Innovative Teaching Tools and Technologies
Topic 4	*language, improve, study, writing, generate, tools, essay, thinking, help, access*	AI-assisted Writing and Learning Tools
Topic 5	*chatgpt, write, academic, cheating, ask, plagiarism, ethics, problem, school, ai*	Ethics and Academic Integrity in AI Usage

The topic probabilities provide a quantitative measure of the prevalence of each theme within the YouTube video transcripts discussing ChatGPT's impact on education. Topic 1, “Future of AI and Human Intelligence,” had a probability of 0.100874, indicating a moderate level of discussion about the long-term implications of AI. Topic 2, “AI in Education and Learning Enhancement,” has a higher probability of 0.268106, reflecting significant interest in the potential benefits of AI in educational contexts. The most prominent theme is Topic 3, “Innovative Teaching Tools and Technologies,” with a probability of 0.365423, highlighting extensive discourse on the integration of AI tools like ChatGPT in teaching. Topic 4, “AI-assisted Writing and Learning Tools,” has a lower probability of 0.077069, suggesting less frequent but still notable discussions on AI's role in aiding writing and other academic tasks. Topic 5, “Ethics and Academic Integrity in AI Usage,” with a probability of 0.186059, underscores substantial concern over ethical issues and the integrity of academic work in the context of AI usage.

Further, the multidimensional scaling (MDS) visualization of these topics indicates that Topics 2, 3, and 5 occupy most of the conceptual space, emphasizing the prominence of discussions about AI's role in education and learning enhancement, innovative teaching tools, and ethical considerations. This distribution reflects a strong public interest in both the transformative potential of AI in education and the ethical dilemmas it presents. Understanding these themes and their prevalence offers valuable insights into the current public discourse on AI in education, guiding future research, policy-making, and ethical frameworks in the integration of AI technologies in educational contexts.

Table 3. Average Topic Probability

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
0.100874	0.268106	0.365423	0.077069	0.186059

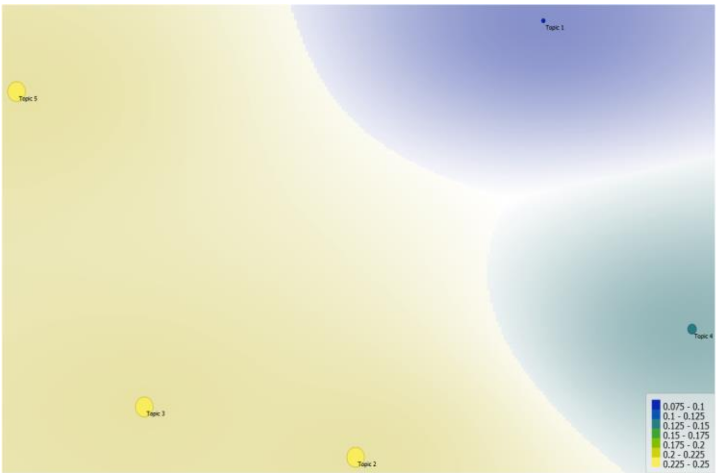

Figure 5. Mutidimentional Scaling of the Topics

The theme delves into the broader implications of integrating AI into human lives, with potential shifts in how we perceive intelligence and the ways AI might augment human abilities. Jarrahi and Lutz [32] said that human-augmented AI and augmented human intelligence can augment their capabilities and intelligence through synergistic human-AI interactions. Artificial intelligence systems have integrated into daily life, with some even allowing themselves to be “programmed” by AI-based applications. AI aids people in various activities and has recently focused on managing the exponential growth of data. The future of AI raises questions about creating machines more intelligent than humans and the compatibility of this with human and planetary sustainability [33]. Zohuri and Rahmani [34] mentions that future of autonomy emphasizes a partnership between humans and AI, transforming industries like manufacturing, e-commerce, and banking. Companies are investing in both manned and unmanned systems to enhance capabilities, recognizing the importance of effective human-machine collaboration. This partnership relies on trust, enabling each to perform optimally, and AI helps systems operate efficiently in challenging conditions. Embracing AI is inevitable for cost-effectiveness and profitability, necessitating adaptation and workforce education. AI enhances human safety and decision-making, benefiting military, commercial, and other sectors.

AI technologies, such as ChatGPT, are increasingly being integrated into educational systems to improve learning experiences and outcomes. The rapid development of AI technologies, such as ChatGPT, has significantly impacted education and academic research by providing personalized learning experiences, automating administrative tasks, and revolutionizing literature review processes. ChatGPT enhances student engagement, aids educators, and facilitates cross-disciplinary research collaborations. However, addressing ethical concerns like misinformation and bias is crucial to ensure transparent AI interactions and promote digital literacy [35]. Aguiar [36] said that the integration of AI-based tools in education is strengthening, with ChatGPT emerging as a popular tool to enhance learning and teaching efficiency. Baidoo-anu and Ansah [2] further explained that ChatGPT and related generative AI technologies enhance education by providing personalized tutoring, automating essay grading with high accuracy, facilitating language translation, supporting interactive learning experiences, and adapting teaching methods based on student performance.

Artificial Intelligence (AI) has emerged as a transformative tool in education, offering innovative ways to enhance teaching practices and improve learning outcomes. One significant advantage of AI in education is its ability to facilitate personalized learning experiences. By analyzing vast amounts of student data, AI algorithms can tailor instruction to meet individual needs and learning styles, thereby optimizing the learning process [37].

This adaptability not only fosters greater engagement but also supports students in mastering concepts at their own pace. AI tools influence teaching methods, student engagement, learning outcomes, and the overall educational environment [38]. Artificial intelligence (AI) is reshaping education by enabling personalized learning through tailored instruction and feedback based on individual student data, thereby promoting inclusivity and addressing diverse learning needs. AI-driven adaptive learning systems also play a crucial role in identifying and filling learning gaps, supporting struggling students with targeted interventions. Moreover, AI enhances collaborative learning environments by facilitating communication, coordination, and knowledge sharing among students, fostering inclusivity by valuing diverse perspectives and skills in group settings. Additionally, AI-powered assistive technologies improve accessibility for students with disabilities through features like captioning and translation, ensuring equitable educational opportunities for all learners [39].

AI-assisted writing and learning tools represent a significant advancement in education, offering novel ways to enhance students' academic skills and learning experiences. These tools, exemplified by platforms like ChatGPT, leverage artificial intelligence to support various aspects of writing and learning [40]. One key benefit is their ability to assist students in generating and refining written content. AI algorithms can analyze text, suggest improvements in grammar and style, and provide real-time feedback, thereby helping students to develop stronger writing skills and produce higher-quality academic work [41]. AI-powered learning tools facilitate personalized learning experiences by adapting to individual student needs and learning paces [42]. They can offer tailored exercises, quizzes, and study materials based on students' strengths and weaknesses, fostering a more efficient and effective learning process. This personalized approach not only enhances student engagement but also promotes deeper understanding and retention of academic content. AI assists educators by automating time-consuming tasks such as grading and assessment. By using AI to evaluate assignments and exams, teachers can save valuable time, allowing them to focus on more interactive and meaningful interactions with students. This automation also ensures more consistent and objective grading practices, benefiting both students and teachers alike [43].

Ethics and academic integrity in the usage of AI represent critical considerations as artificial intelligence technologies increasingly permeate educational settings. This theme underscores the importance of addressing ethical implications and ensuring responsible AI deployment to uphold academic standards and values. Key concerns include the potential for AI to facilitate academic dishonesty, such as plagiarism and cheating, through its ability to generate and manipulate text. Westfall [44] mentioned that educators Battle Plagiarism as 89% of Students Admit to using OpenAI’s ChatGPT for Homework. Safeguarding against these risks requires robust measures for detecting and preventing misuse, as well as educating students about ethical conduct in using AI and AI-detecting tools [45].

The ethical dimensions extend to issues of bias and fairness in AI algorithms used for assessment and decision-making. Biased algorithms can perpetuate inequalities by disadvantaging certain groups or favoring specific demographics, posing challenges to equitable educational outcomes. Addressing these biases necessitates transparency in AI development, rigorous testing for fairness, and ongoing monitoring to mitigate unintended consequences [46]. Based on these results and findings, several recommendations can be made. Educational institutions should develop and implement clear policies to maintain academic integrity while utilizing AI technologies, including guidelines on acceptable use and detection of AI-generated content. Professional development initiatives should be established to equip educators with the skills necessary to effectively integrate AI tools into their teaching practices. Ongoing research should focus on understanding the long-term impacts of AI on educational outcomes and exploring methods to mitigate ethical concerns, such as bias and privacy issues. Finally, fostering a culture of transparency around AI applications in education will help build trust among stakeholders and encourage responsible AI use.

4. CONCLUSION

The integration of AI technologies in education presents both transformative opportunities and significant ethical considerations. The analysis reveals that AI's potential to enhance learning experiences, personalize education, and improve administrative efficiency is widely recognized and positively received. However, concerns regarding academic integrity, such as cheating and plagiarism, highlight the need for robust policies and ethical guidelines to prevent misuse. The research also recommends the establishment of an Adaptive Learning Framework and AI Ethics in Education Model, which emphasizes the importance of personalized learning experiences. In this model, AI systems continuously analyze student interactions to tailor content delivery and assessments to individual learning styles and performance. Simultaneously, it advocates for structured ethical guidelines and policies to address dilemmas posed by AI, such as academic integrity and data privacy. The prevalence of discussions around future impacts and improvements underscores optimism about AI's long-term benefits for teaching methodologies and learning outcomes. Ensuring equitable access to AI tools and addressing the digital divide are critical for maximizing these benefits. Therefore, educators, policymakers, and technology developers must collaborate to establish transparent, fair, and responsible AI practices that uphold academic integrity, protect data privacy, and promote inclusivity in educational environments. This balanced approach will enable the education sector to harness the full potential of AI while mitigating its potential drawbacks, ultimately fostering a more adaptive, engaging, and effective learning landscape.

ACKNOWLEDGEMENTS

We would like to thank all parties who have contributed, either directly or indirectly, to the implementation of this research.

REFERENCES

[1] M. Philogene, S. Zhiyuan, and P. Nyoni, "Teacher professionalism development in TVET system: Preparedness, In-Service trainings and challenges", *Journal Evaluation in Education (JEE)*, vol. 5, no. 3, pp. 107-117, 2024, doi: 10.37251/jee.v5i3.967.

[2] D. Baidoo-Anu, and L. O. Ansah, "Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning", *Journal of AI*, vol. 7, no. 1, pp. 52-62, 2023, doi: 10.61969/jai.1337500.

[3] A. Johri, A. S. Katz, J. Qadir, and A. Hingle, "Generative artificial intelligence and engineering education", *Journal of Engineering Education*, vol. 112, no. 3, pp. 572-577, 2023, doi: 10.1002/jee.20537.

[4] M. Jovanović, and M. Campbell, "*Generative Artificial Intelligence: Trends and Prospects"*, 2022, doi: 0.1109/MC.2022.3192720.

[5] L. Hu, "*Generative AI and Future<*", 2023, Retrieved on January 23 from https://pub.towardsai.net/generativeai-and-future-c3b1695876f2.

[6] OpenAI. Available online: https://openai.com (accessed on 12 March 2024).

[7] C. K. Lo, "What is the impact of ChatGPT on education? A rapid review of the literature", *Education Sciences*, vol. 13, no. 4, pp. 410, 2023, doi: 10.3390/educsci13040410.

[8] J. Crawford, M. Cowling, and K. Allen, "Leadership is needed for ethical ChatGPT: Character, assessment, and learning using Artificial Intelligence (AI)," *Journal of University Teaching & Learning Practice*, vol. 20, no. 3, pp. 1-21, 2022, doi: 10.53761/1.20.3.02.

[9] J. Qadir, "Engineering Education in the Era of ChatGPT: Promise and Pitfalls of Generative AI for Education", TechRxiv Prepr. 2022, doi: 10.36227/techrxiv.21789434.

[10] M. M. Rahman, and Y. Watanobe, "ChatGPT for education and research: Opportunities, threats, and strategies", *Applied Sciences*, vol. 13, no. 9, pp. 5783, 2023, doi: 10.3390/app13095783.

[11] S. Shahriar, and K. Hayawi, "Let's have a chat! A conversation with ChatGPT: Technology, applications, and limitations. arXiv preprint", arXiv:2302.13817, doi: 10.48550/arXiv.2302.13817.

[12] P. Limna, T. Kraiwanit, K. Jangjarat, P. Klayklung, and P. Chocksathaporn, "The use of ChatGPT in the digital era: Perspectives on chatbot implementation", *Journal of Applied Learning and Teaching*, vol. 6, no. 1, 2023, doi: 10.37074/jalt.2023.6.1.32

[13] J. A. Lossio-Ventura, R. Weger, A. Y. Lee, E. P. Guinee, J. Chung, L. Atlas,... and F. Pereira, "A comparison of chatgpt and fine-tuned open pre-trained transformers (opt) against widely used sentiment analysis tools: Sentiment analysis of covid-19 survey data", *JMIR Mental Health*, 11, e50150, 2024, doi: 10.2196/50150

[14] J. W. Creswell, "*Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*", Sage Publications, USA, 2023.

[15] L. J. B. Caluza, "Deciphering published articles on cyberterrorism: A latent Dirichlet allocation algorithm application", *International Journal of Data Mining, Modelling and Management*, vol. 11, no. 1, pp. 87-101, 2019.

[16] S. Vijayarani, M. J. Ilamathi, and M. Nithya, "Preprocessing techniques for text mining-an overview," *International Journal of Computer Science & Communication Networks*, vol. 5, no. 1, pp. 7-16, 2015

[17] C. Ramasubramanian, and R. Ramya, "Effective pre-processing activities in text mining using improved porter‟s stemming algorithm", *International Journal of Advanced Research in Computer and Communication Engineering*,vol. 2, no. 12, 2013.

[18] A. Alfajri, D. Richasdy, and M. A. Bijaksana, "Topic modelling using Non-Negative Matrix Factorization (NMF) for telkom university entry selection from instagram comments", *Journal of Computer System and Informatics (JoSYC)*, vol. 3, no. 4, pp. 485-492, 2022, doi: 10.47065/josyc.v3i4.2212.

[19] R. K. Mishra, S. Urolagin, J. A. Jothi, A. S. Neogi, and N. Nawaz, "Deep Learning-based Sentiment Analysis and Topic Modeling on Tourism During Covid-19 Pandemic", *Front. Comput. Sci*. 3:775368, 2022, doi: 10.3389/fcomp.2021.775368.

[20] V. Bonta, N. Kumaresh, and N. Janardhan, "A comprehensive study on lexicon based approaches for sentiment analysis", *Ajcst*, vol. 8, n.o. (S2), 1–6, 2019, doi:10.51983/AJCST-2019.8.S2.2037

[21] N. Swarnkar, "VADER Sentiment Analysis: A Complete Guide, Algo Trading and More", (2020, March 21). Retrieved from Quantinsti: https://blog.quantinsti.com/vader-sentiment/

[22] A. Farkhod, A. Abdusalomov, F. Makhmudov, and Y. I. Cho, "LDA-based topic modeling sentiment analysis using topic/document/sentence (TDS) model", *Applied Sciences*, vol. 11, no. 23, pp. 11091, 2021, doi: 10.3390/app112311091.

[23] A. Agarwal, B. Xie, I. Vovsha, O, Rambow, R. J. Passonneau, "Sentiment analysis of twitter data", *In Proceedings of the Workshop on Language in Social Media (LSM 2011)*, Portland, Oregon, 23 June 2011.

[24] V. Eidelman, J. Boyd-Graber, P. Resnik, "Topic models for dynamic translation model adaption", *In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics* (Volume 2: Short Papers), Jeju Island, Korea, 8–14 July 2012.

[25] P. van Kessel, "Interpreting and validating topic models", (2019, August 2). Retrieved from Medium: https://medium.com/pew-research-center-decoded/interpreting-and-validating-topic-models-ff8f67e07a32

[26] J. Demšar, T. Curk, A. Erjavec, C. Gorup, T. Hočevar, M. Milutinovič,... and B. Zupan, "Orange: data mining toolbox in Python", *the Journal of machine Learning research*, vol. 14, no. 1, pp. 2349-2353, 2013.

[27] B. U. Zaman, "Transforming education through ai, benefits, risks, and ethical considerations", *Authorea Preprints*, 2023, doi: 10.36227/techrxiv.24231583.v1

[28] J. Young, "The rise of artificial intelligence in education", *International Journal of Innovative Research and Development*, 2024, doi: https://doi.org/10.24940/ijird/2024/v13/i2/FEB24019

[29] D. R. Cotton, P. A. Cotton, and J. R. Shipway, "Chatting and cheating: Ensuring academic integrity in the era of ChatGPT", *Innovations in education and teaching international*, vol. 61, no. 2, pp. 228-239, 2024, doi: 10.1080/14703297.2023.2190148

[30] J. Miao, C. Thongprayoon, S. Suppadungsuk, O. A. Garcia Valencia, F. Qureshi, and W. Cheungpasitporn, "Ethical dilemmas in using AI for academic writing and an example framework for peer review in nephrology academia: A narrative review", *Clinics and Practice*, vol. 14, no. 1, pp. 89-105, 2023, doi: 10.3390/clinpract14010008

[31] M. Montenegro-Rueda, J. Fernández-Cerero, J. M. Fernández-Batanero, and E. López-Meneses, "Impact of the implementation of ChatGPT in education: A systematic review", *Computers*, vol. 12, no. 8, pp. 153, 2023, doi: 10.3390/computers12080153

[32] M. H. Jarrahi, C. Lutz, and G. Newlands, "Artificial intelligence, human intelligence and hybrid intelligence based on mutual augmentation", *Big Data & Society*, vol. 9, no. 2, 2022, doi: https://doi.org/10.1177/2053951722114282

[33] E. Mercier-Laurent, "The Future of Artificial Intelligence: Empowering Humanity and Help Protecting Planet". *In Computer Sciences & Mathematics Forum* (Vol. 8, No. 1, p. 38), (2023, August). MDPI, doi: 10.3390/cmsf2023008038

[34] B. Zohuri, and F. M. Rahmani, F. M. "Artificial intelligence versus human intelligence: A new technological race", *Acta Scientific Pharmaceutical Sciences*, vol. 4, no. 5, 2020, doi: 10.31080/ASPS.2020.04.0530

[35] A. de Oliveira Silva, and D. dos Santos Janes, "The emergence of ChatGPT and its implications for education and academic research in the 21st century", *Review of Artificial Intelligence in Education*, vol. 2, pp. e06-e06, 2021, doi: 10.37497/rev.artif.intell.education.v2i00.6

[36] J. J. B. Aguiar, "ChatGPT as an educational support tool: an analysis of its potential in the teaching and learning process", *Caderno Pedagógico*, vol. 21, no. 2, pp. e2660-e2660, 2024, doi: 10.54033/cadpedv21n2-019.

[37] N. C. A. Ashwini, N. M. N. Kumar, and S. V, "Leveraging artificial intelligence in education: Transforming the learning landscape", *International Research Journal of Computer Science*, 2023, doi: 10.26562/irjcs.2023.v1005.16

[38] D. Z. Obidovna, "The pedagogical-psychological aspects of artificial intelligence technologies in integrative education", *International Journal Of Literature And Languages*, vol. 4, no. 3, pp. 13-19, 2024, doi: 10.37547/ijll/Volume04Issue03-03

[39] O. O. Adeleye, C. A. Eden, and I. S. Adeniyi, "Innovative teaching methodologies in the era of artificial intelligence: A review of inclusive educational practices", *World Journal of Advanced Engineering Technology and Sciences*, vol. 11, no. 2, pp. 069-079, 2024, doi: 10.30574/wjaets.2024.11.2.0091.

[40] C. Song, and Y. Song, "Enhancing academic writing skills and motivation: assessing the efficacy of ChatGPT in AI-assisted language learning for EFL students", *Frontiers in Psychology*, vol. 14, pp. 1260843, 2023, doi: 10.3389/fpsyg.2023.1260843

[41] L. Wu, "AI-based writing tools: Empowering students to achieve writing success", *Advances in Educational Technology and Psychology*, vol. 8, no. 2, pp. 40-44, 2024, doi: 10.23977/aetp.2024.080206

[42] M. J. K. O. Jian, "Personalized learning through AI", *Advances in Engineering Innovation*, vol. 5, no. 1, pp. 2023, doi: 10.54254/2977-3903/5/2023039

[43] I. Celik, M. Dindar, H. Muukkonen, and S. Järvelä, "The promises and challenges of artificial intelligence for teachers: A systematic review of research", *TechTrends*, vol. 66, no. 4, pp. 616-630, 2022, doi: 10.1007/s11528-022-00715-y.

[44] C. Westfall, "Educators Battle Plagiarism As 89% Of Students Admit To Using OpenAI's ChatGPT For Homework", C. (2023, Jan 28).

[45] P. P. Santra, and D. Majhi, "Scholarly communication and machine-generated text: is it finally ai vs ai in plagiarism detection?. Journal of Information and Knowledge, 175-183, 2023, doi: 10.17821/srels/2023/v60i3/171028.

[46] J. Sreerama, and G. Krishnamoorthy, "Ethical Considerations in AI Addressing Bias and Fairness in Machine Learning Models", *Journal of Knowledge Learning and Science Technology*, vol. 1, no. 1, pp. 130-138, doi: 10.60087/jklst.vol1.n1.p138.